Spring Snowmelt in the Sierra Nevada: Does a Day Make a Difference?

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Daily fluctuations in air temperature can explain much of the variability in snowmelt-driven discharge in the high Sierra Nevada river basins during spring (Dettinger this issue; Cayan this issue). Statistical/dynamical methods appear useful in exploring this linkage between air temperature and discharge in the Merced River basin above Happy Isles, Yosemite National Park, California. As a first step, input (air temperature) is filtered to estimate output (discharge) using constant parameter difference equations (constant over the snowmelt cycle but varying from year-to-year). The discharge response to present and past temperatures determines the filter characteristics. In general, as might be expected, the response is larger in springs following wet than dry winters. In a more realistic model, the parameters are time-varying such as in daily estimates using a Kalman filter. Ultimately, as snowpack wanes, air temperature is less and less "in control" and the time-varying response coefficients decline. Does this phenomenon mark the beginning of summer (*ie*, a hydroclimate "summer transition")? Difference equation models appear to be useful in curve fitting and, at the very least, show the strong connection between air temperature and discharge (which could be exploited for filling gaps in time series, exploring data quality, *etc*). But to the extent air temperature can be predicted, can we also forecast discharge – that is, can useful discharge forecasts extend out as far as temperature forecasts? With each new day, both forecast and model errors accumulate. In a preliminary example, alternating between a Kalman filter to estimate model coefficients and a difference filter to estimate discharge, this method seems useful. Although we are only in the initial stages of developing a reliable prediction scheme, the strong correspondence apparent in daily temperature and streamflow emphasizes "what a difference a day makes".

The Problem

River discharge is a major control on the physics, chemistry, and biology of San Francisco Bay. Management of the bay/delta region often centers on river discharge issues, including salinity penetration. Therefore, the more we know about the causes and consequences of the variations in Central Valley discharge (delta outflow), the less likely management actions are to cause inadvertent problems.

We know only the initial (pre-European settlement) hydrologic condition in much of the Sacramento-San Joaquin watershed via proxy methods. Peeling off the multi-layers of water management and land use effects to "see" the natural variability in discharge at high resolution is, perhaps, almost impossible. However, a major component of discharge is snowmelt, especially in spring. The major processes controlling spring snowmelt are natural and are at high elevations where the gaging stations lie above the fray.

The crown jewel in gage sites for linking atmospheric circulation to discharge through the spring snowmelt signal is the Merced River at Happy Isles, Yosemite National Park (Figure 1). Due to the foresight of early hydrologists, this station has continuous daily records since 1916 (Cobb and Biesecker 1971; Lawrence 1987).

Data and Methods

Air temperature data are a composite index of mean daily values from Sacramento, Tahoe, Nevada City, and Hetch Hetchy (Figure 1), 1932-1993 (Riddle, unpublished). This index is used to represent air temperature variations in the upper Merced Basin. Daily averaged discharge is from the USGS gaging station at Happy Isles.

On average, 95% of the discharge in Merced River above Happy Isles is driven by snowmelt (Clow and others 1996; Cobb and Biesecker 1971) as illustrated in Figure 2 by the wide separation between peaks in precipitation (winter) and discharge (spring). Cayan and others (1993), Cayan (1996), and Dettinger and Cayan (1995) provide details on the temporal/spatial relationships between snowmelt-driven (high elevation) and rainfall-driven (low elevation) discharge. Morris (1985) provides an overview of snowmelt. Water year days 165 (March 13) through 285 (July 12) were selected for study; this period generally encompasses the rise and decline in snowmelt-driven discharge.

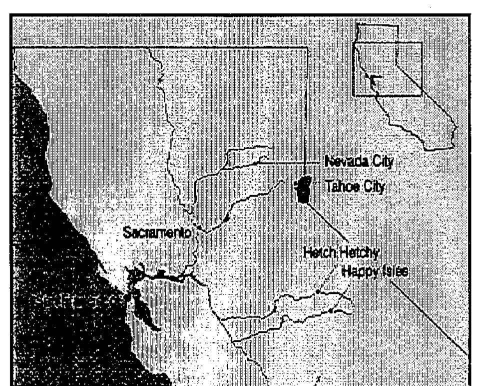

Figure 1
STUDY AREA, METEOROLOGICAL AND RIVER GAGE SITES

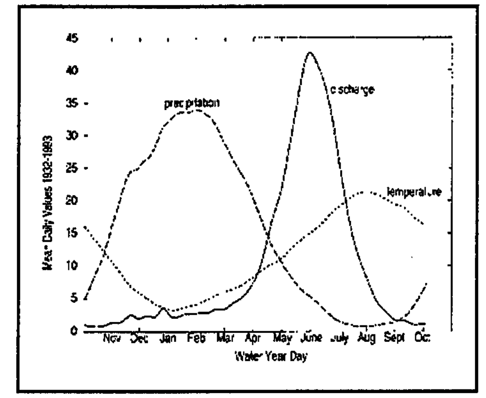

Figure 2
LOW-PASS FILTERED AIR TEMPERATURE, PRECIPITATION, AND DISCHARGE
Double-pass boxcar filter to preserve phase: 15 days for air temperature; 25 days for precipitation; 9 days for discharge. Precipitation and air temperature from a mean-daily index: Sacramento, Tahoe, Nevada City, and Hetch Hetchy. Discharge from Merced River, Happy Isles, Yosemite National Park, California.

Our focus is on the air temperature/discharge linkage and mostly for the high snowpack/high discharge years. Given the system complexity, it may seem unexpected that linear methods capture most of the discharge variance using only air temperature as input. One statistical approach is the use of a difference equation to estimate output (discharge) from filtered input (temperature) and, possibly, past output (Equation 1):

$$Q[n]=\sum_{i=1}^{N} a_i = Q[n-_i]+\sum_{i=0}^{M} b_i T[n-_i]$$

Where:

[n] is the time index,

a_i are the past discharge (Q) coefficients, and

b_i are the present and past temperature (T) coefficients.

In the simplest case, discharge is estimated by multiplying the corresponding coefficients with air temperature and summing. Each day's discharge is based on the temperature for the present and past 2 or 3 days (ultimately the past temperature signal fades into model noise).

In a more realistic model, the coefficients, b_i, vary with time. A Kalman filter (Ljung 1995, 1987; Brown and Hwang 1977) is one approach to estimate the time-varying parameters. Kalman filter methods are a well defined way to pick optimum coefficients; for details, see the above references. The filter recursively estimates how past values of air temperature and discharge should be weighted to produce an optimal estimate of discharge given errors in both the observations and the filter (the model). The Kalman filter method used here is a 1-day forecast (Ljung 1995, 1987).

In attempting to predict discharge beyond 1 day, the new estimates of the coefficients must be based on simulated (by equation 1) rather than observed discharge. The Kalman filter gives daily estimates of discharge and time-varying parameters. The first step in prediction is to estimate the coefficients used to calculate discharge. This starting point was arbitrarily selected here as day 225. The coefficients for day 225 are used in the difference equation with day 226 temperature to estimate day 226 discharge. This estimated discharge is then fed back into the Kalman filter to estimate a new set of coefficients (and discharge) for day 226, which are again fed into the equation. This procedure is repeated, increasing the forecast time in this example to 8 days.

Results

We first illustrate a simple example using constant parameters (constant b_i values in the equation). These parameters were identified using an instrumental variable method that squeezes the maximum correlation out of temperature or temperatures and past discharge (Ljung 1995, 1987).

As expected, the simulated discharge values are too high in late winter/early spring and too low later (Figure 3). This is partly because the parameters represent an average over conditions where the days are becoming longer and the nights warmer as spring progresses (the snowpack is also accumulating thermal energy). Therefore the response is first over- and then underestimated.

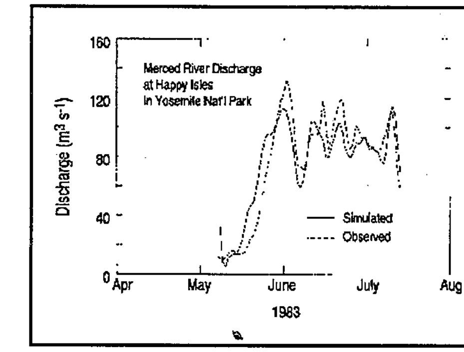

Figure 3
OBSERVED AND SIMULATED DISCHARGE USING A CONSTANT PARAMETER MODEL, MERCED RIVER AT HAPPY ISLES, 1993

The next example, a variable parameter Kalman filter analysis, may seem like cheating because we are curve fitting with time-varying parameters. The parameter averages follow different cycles depending on wetness and dryness and lead/lag relationships (not shown). The parameters provide predictive power only after a series of air temperature and discharge fluctuations have already occurred (after observed discharge is compared to air temperature). About all that is known in advance is whether the previous winter was wet or dry. At least this objectively identifies when the filter gain (coefficient sum) begins to decrease due to a limited snowpack, such as June 1 for the average of the 10 wettest years, 1932-1993 (excluding the 2 wettest years, 1983 and 1969), and May 16 for the driest (Figures 4 and 5).

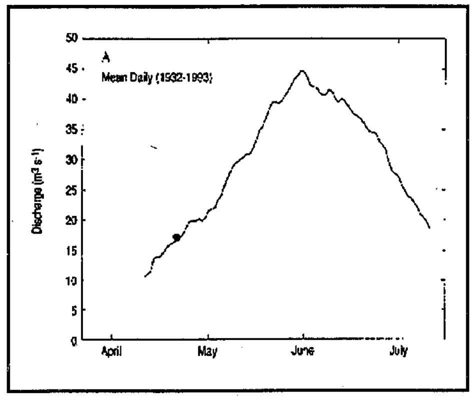

Figure 4
MEAN DAILY DISCHARGE, 1932-1993, DURING AND FOLLOWING THE MEDIAN DAY OF SNOWMELT "PULSE" (April 19) UP TO ONSET OF THE SUMMER TRANSITION

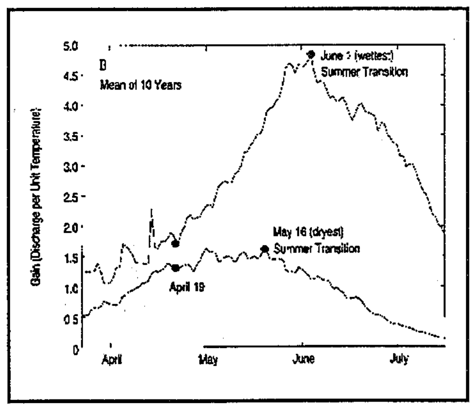

Figure 5
AVERAGE DAY OF THE SUM OF DAILY RESPONSE COEFFICIENTS, bi, BEFORE THE SUMMER TRANSITION IN A WET AND DRY 10-YEAR COMPOSITE

Our last example is an initial attempt to use these methods in a prediction mode. At some point only predicted (rather than observed) air temperatures will be included in the modeling scheme. To keep this simple, we are assuming the observed air temperature values are predicted values. Therefore, the results are better than can be expected using true predictions of air temperature. This assumption is of minor significance here, because assessment of prediction error in air temperature (which is very small) is a different issue. Here we are attempting to predict discharge solely on the basis of air temperature and past estimates of discharge to advance the predictions one day at a time.

When the time series are extended to an 8-day forecast, these initial results appear to be reasonable (Figure 6). Beyond day 3 the parameters (b_i) continue to change but are based solely on predicted values of temperature (assumed) and discharge.

If the parameter changes were small over the 8-day window of forecasting, a constant parameter model might be an adequate method of approximation (*ie*, Figure 3). But we would only know that after the fact (*ie*, hindcasting).

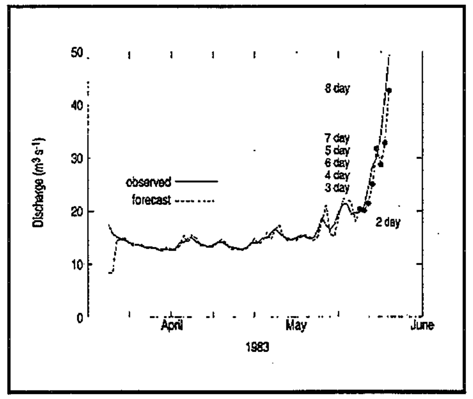

Figure 6
FORECAST OF MERCED RIVER DISCHARGE AT HAPPY ISLES, WITH 1-DAY FORECAST DAY 225, 2-DAY ON 226, 3-DAY ON 227, ETC.
Note divergence around the 5-day forecast between observed and forecasted.

Discussion

The basic evolution of a spring snowmelt cycle in the West seems to start with a change in atmospheric circulation. A low pressure (winter) pattern is replaced (within days) by a strong and expanding high pressure pattern, accompanied by high air temperature and a persistent surge in snowmelt-driven discharge (Cayan, this issue). This, at least for purposes of discussion, might be called a hydroclimatic spring transition (Figure 4). This transition may or may not show a relationship to the presumably more fickle oceanographic/ atmospheric spring transition. (Strub *et al* (1985) discuss the oceanographic spring and fall transition.)

Following the typical strong surge in discharge, the temperature response coefficients (b_i) in the equation largely track the rise in discharge as temperature increases its control over the snowmelt process. At some point the system is saturated (the rise in coefficients tends to flatten out). This phase is followed by a steady decline. This point of the decline, where the sum of the coefficients (or gain) decreases, might be a summer transition (Figure 5). We are not aware of an oceanographic counterpart summer transition.

The initial stages of forecasting spring snowmelt discharge using statistical/dynamical time series are encouraging. These methods provide some insight into the response characteristics of the system, but we need to test further the forecasting power in our data-derived coefficients (Dettinger, this issue). We know the coefficients vary from year-to-year and tend to be higher in wet than in dry years. The alternating use of a Kalman filter with the difference equation appears to extend forecasts beyond low-risk 1-day forecasts, which use only observed discharge values. Also, multi-parameter models such as input of the daily variations in high-elevation snowpack as well as air temperature, may better constrain predictions, but such records are short. As the model complexity increases, it makes more sense to use physically based models (Jeton and Smith 1993; Jeton *et al* 1996). In closing, we have only scratched the surface, and there are many options.

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Sampling for Zooplankton in the Lower Estuary

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This report describes results to date of the zooplankton pilot study begun in spring 1997. The objectives of this study are to answer these questions:

- What changes have occurred in the zooplankton of the lower estuary since the previous survey, conducted in 1978-1981?
- What sampling design would represent the zooplankton of the lower estuary most cost-effectively in a long-term monitoring program?
- What species (or larger taxonomic groupings) are important in the lower estuary, and what is their distribution in space and time?

The study design calls for initial sampling to determine the best sampling strategy to account for vertical and lateral variability in abundance. At present we are finishing this initial phase. A large part of the work in this phase has been in training assistants to identify the species occurring in this area. Because plankton can freely enter the bay from the coastal ocean, the potential species diversity is much higher than in the regions of the upper estuary now being sampled frequently. This diversity suggests caution in assigning names to specimens until the counters gain familiarity with the whole suite of species likely to be encountered.

The USGS sampled for zooplankton in 1978-1991 (Ambler *et al* 1985). Part of the rationale for this study is to detect changes since the USGS sampling that result from introductions of zooplankton and possibly from grazing by *Potamocorbula amurensis.* Other current sampling efforts will provide additional information: Dr. Steve Bollens (RTC) has been sampling on monthly cruises of R/V *Polaris*, and we may analyze some of those samples to supplement samples we will begin taking on the Bay Study surveys. His assistant, Jeff Cordell of the University of Washington, has provided an initial list of species from the Gulf of the Farallones, which will prove useful in analyzing samples, particularly from the Central Bay. NMFS is taking samples with a 500 μm mesh net in Central Bay, and identifications resulting from these samples (by Tony Chess) will be useful as well.

We have conducted two sampling cruises on R/V *Questuary* and two on an outboard boat. On the *Questuary* cruises (April and May) we sampled along transects across the bay (South, Central, and San Pablo, the latter omitted in April because of a vessel breakdown). On each transect we took both vertical and surface tows at stations deeper than about 3 meters and oblique tows at other stations. In the third cruise (June) we took several samples for identification, eight replicate vertical tows for examination of sampling variability, and samples for analyzing size classes of copepods. The fourth cruise, from which analysis is incomplete, was for further sampling for identification and to conduct a transect into shallow water in San Pablo Bay to determine whether zooplankton in this region is depauperate (as has been found in other shallow areas).

Abundant Species

Species identifications so far are tentative. In general, results to date are similar to those presented by Ambler *et al* (1985) except for two introduced species, the copepods *Tortanus dextrilobatus* and *Pseudodiaptomus marinus*. It is too early to tell if abundance of common species such as copepods of the genus *Acartia* is